introduction to recommender systems

Carlos Soares

(adapted from materials from the book
“Recommender Systems – An Introduction” by
Dietmar Jannach, Markus Zanker, Alexander Felfernig, Gerhard Friedrich
Cambridge University Press)

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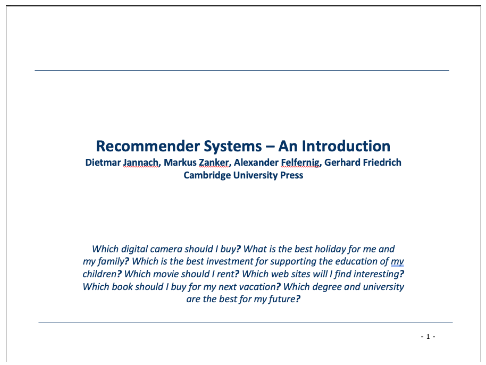
Recommender Systems – An Introduction
Dietmar Jannach, Markus Zanker, Alexander Felfernig, Gerhard Friedrich
Cambridge University Press

Which digital camera should I buy? What is the best holiday for me and my family? Which is the best investment for supporting the education of my children? Which movie should I rent? Which web sites will I find interesting? Which book should I buy for my next vacation? Which degree and university are the best for my future?

- 1 -

plan

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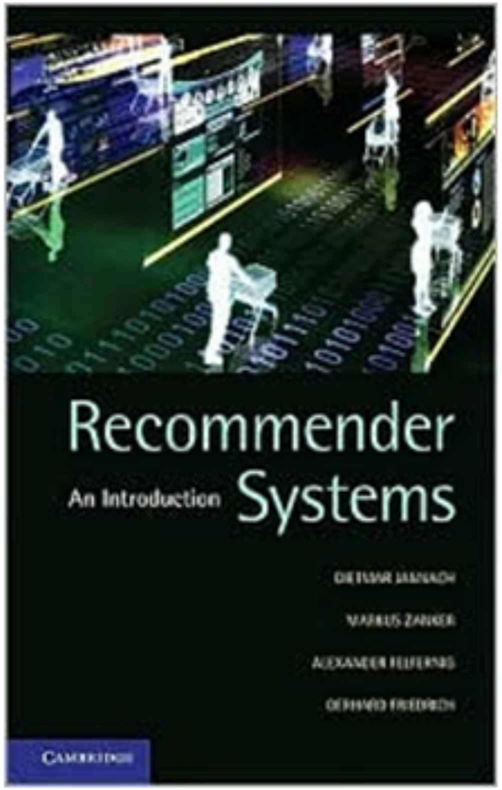
- introduction
  - problem domain
  - purpose and success criteria
  - paradigms of recommender systems
- collaborative filtering
- evaluation
- data
- more algorithms
- challenges

[redacted]



Recommender Systems: An Introduction

by Dietmar Jannach, Markus Zanker, Alexander Felfernig, Gerhard Friedrich

AVERAGE CUSTOMER RATING:

(Be the first to review)

Gefällt mir   Registrieren, um sehen zu können, was deinen Freunden gefällt.

FORMAT:
Hardcover

NOOKbook (eBook) - not available
Tell the publisher you want this in NOOKbook format

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~~$65.00~~ List Price
$52.00 Online Price
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Add to Cart

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Table of Contents

Customers who bought this also bought

Purpose and success criteria (1/2)

- Retrieval
  - Users know in advance what they want
  - Provide "correct" proposals
  - Reduce search costs
- Recommendation
  - Items unknown to users
  - Serendipity
- Prediction
  - Predict to what degree users like an item
- Interaction
  - Give users a "good feeling"
  - Convince/persuade users - explain
- Conversion
  - Increase "hit", "clickthrough", "lookers to bookers" rates
  - Optimize sales margins and profit

Serendipity and the Long Tail [or why the best place to hide a dead body is the 2nd page of results of google search]

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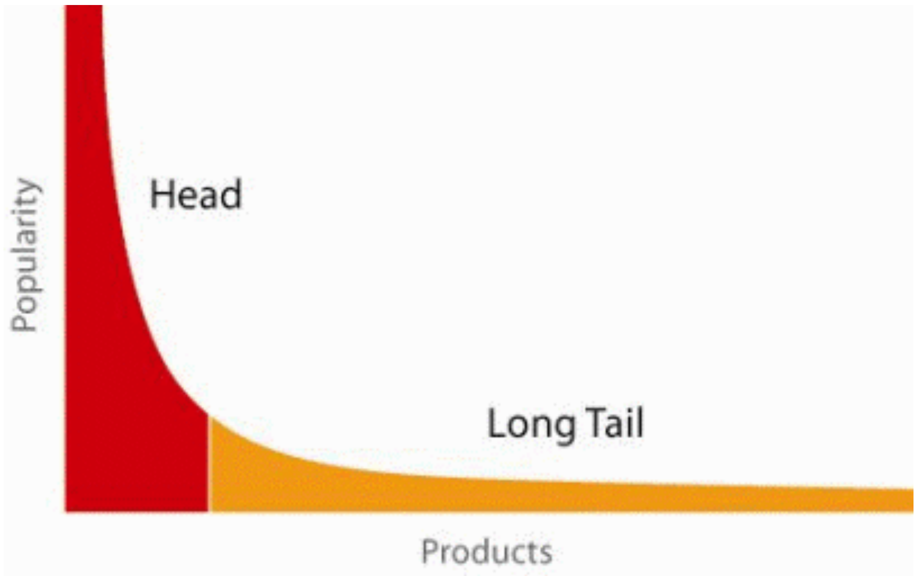
- Recommend widely unknown items that users might actually like!

- 20% of items accumulate 74% of all positive ratings



Recommender systems: definition

- Given
  - User model
    - e.g. ratings, preferences, demographics, situational context
  - Items
    - with or without description of item characteristics
- Find
  - Relevance score
  - Typically used for ranking

- Relation to Information Retrieval
  - IR is finding material [..] of an unstructured nature [..] that satisfies an information need from within large collections [..].

(1) Manning, Raghavan, and Schütze, *Introduction to information retrieval*, Cambridge University Press, 2008

Paradigms of recommender systems

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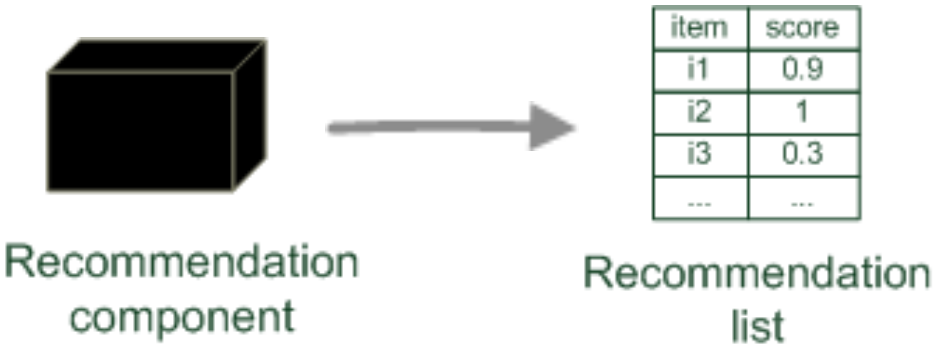
Recommender systems reduce information overload by estimating relevance



Paradigms of recommender systems

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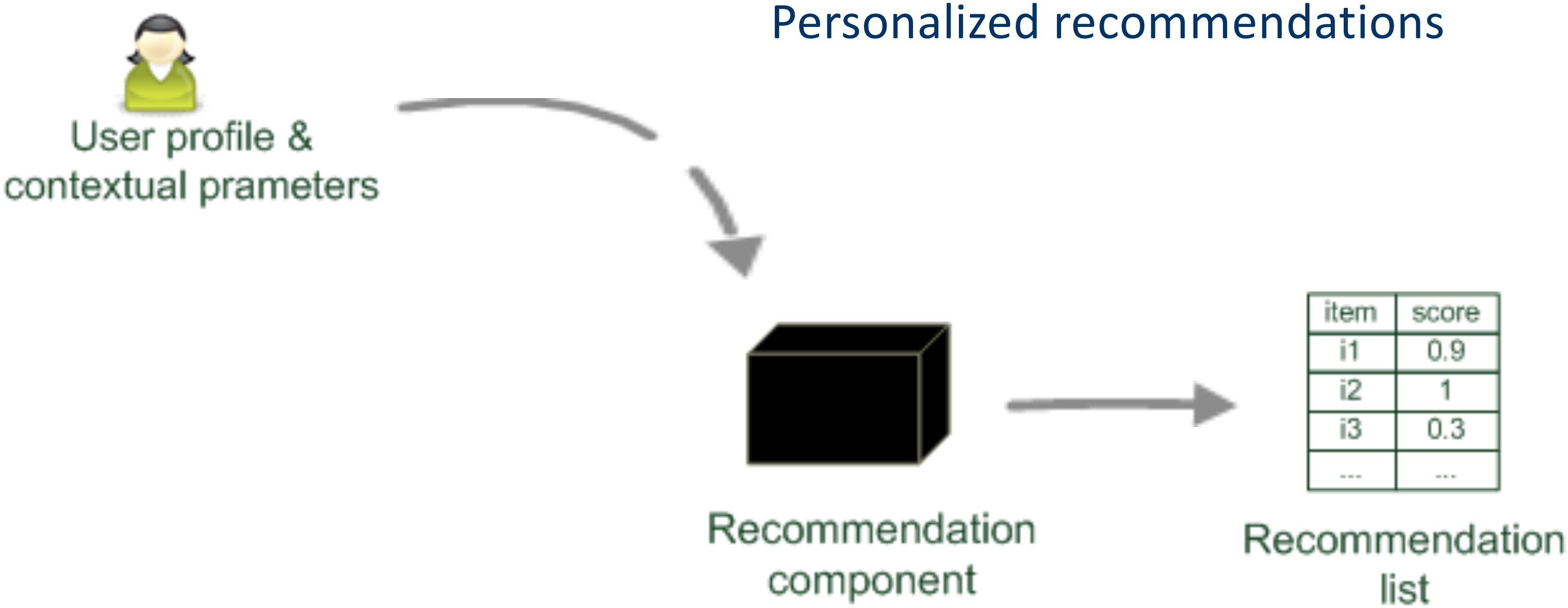
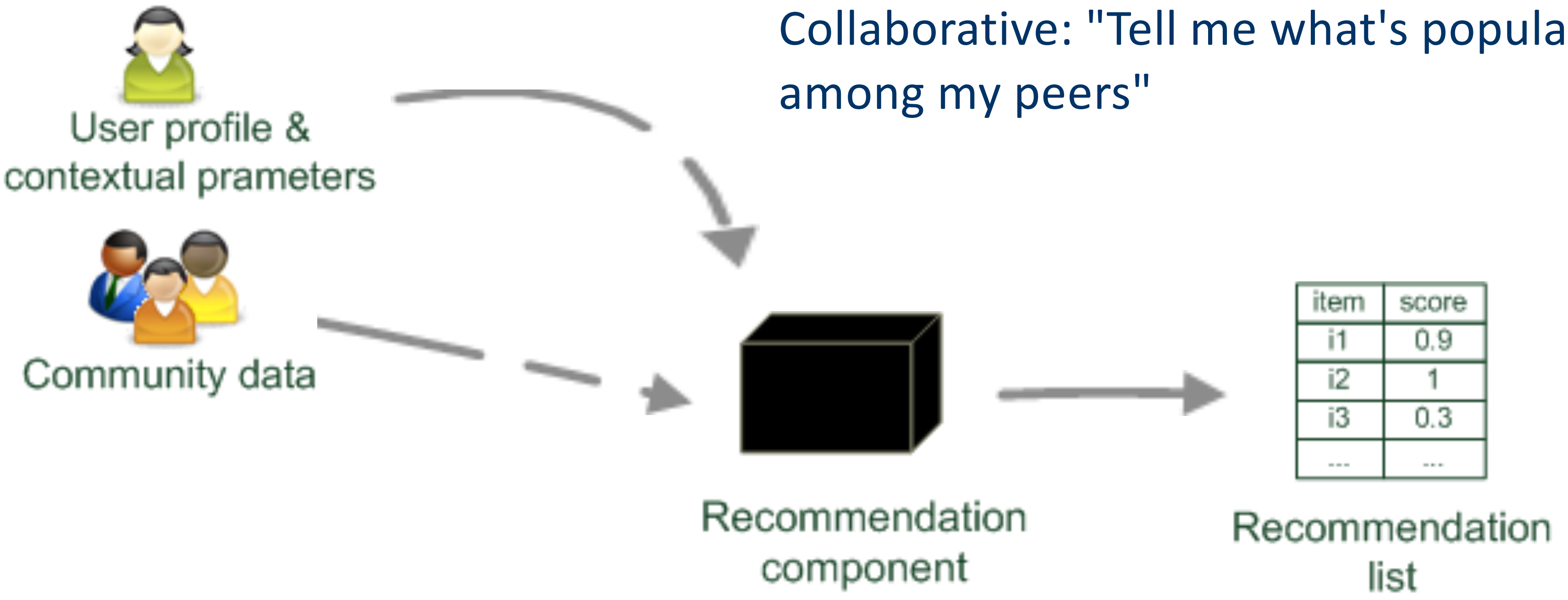
Personalized recommendations



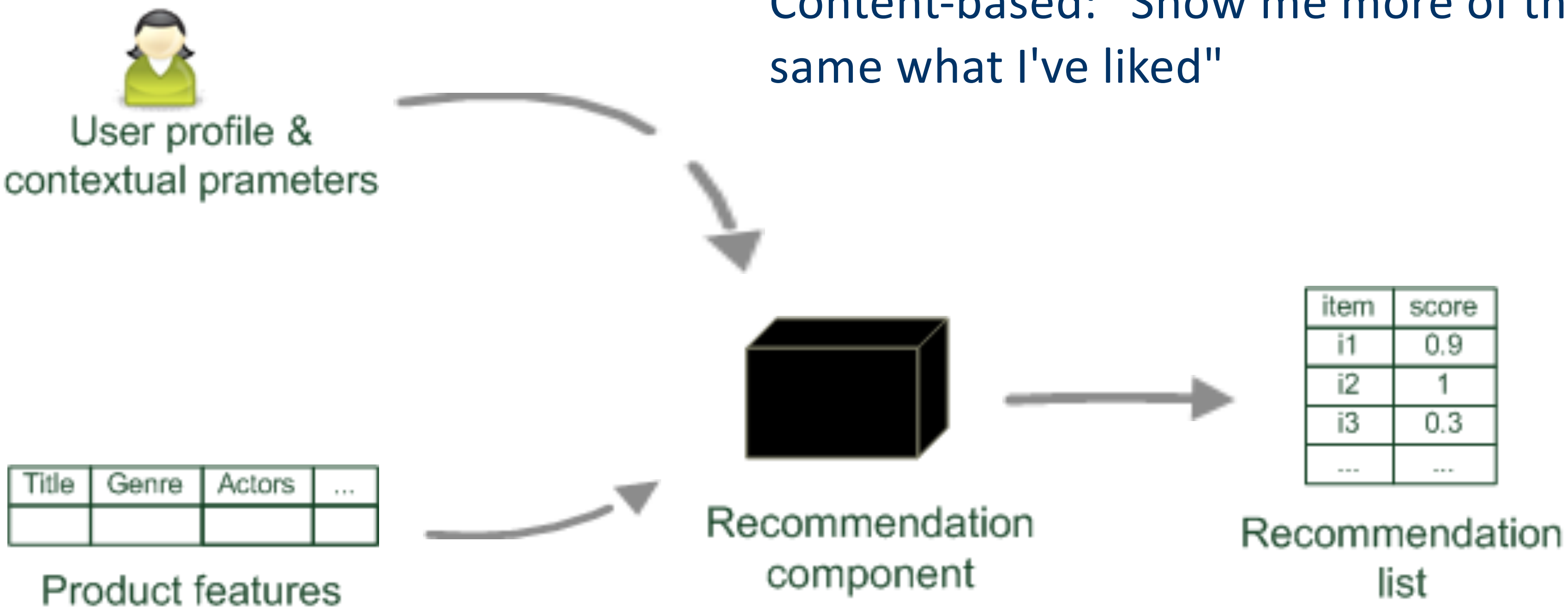
Paradigms of recommender systems

Collaborative: "Tell me what's popular among my peers"



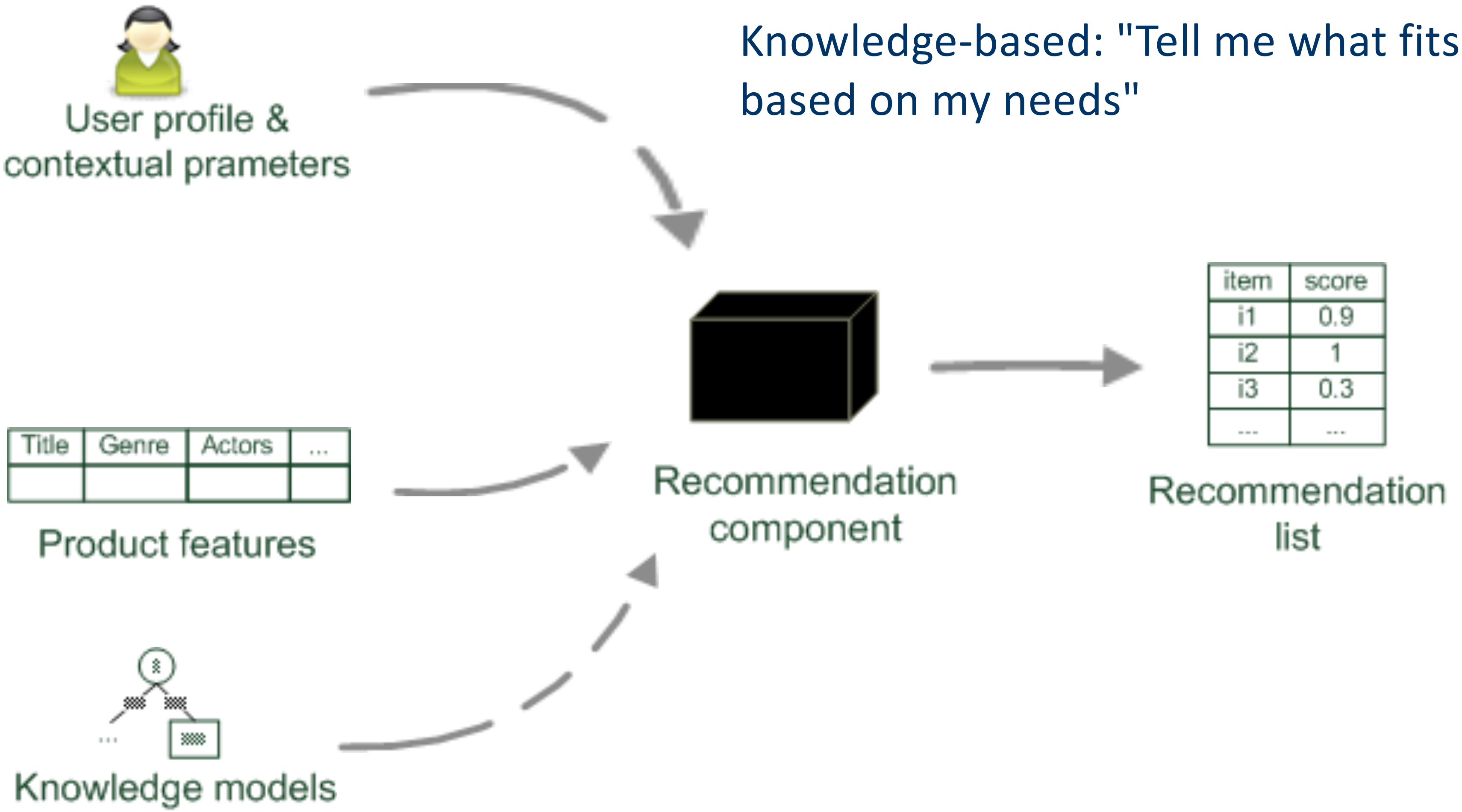
Paradigms of recommender systems

Content-based: "Show me more of the same what I've liked"



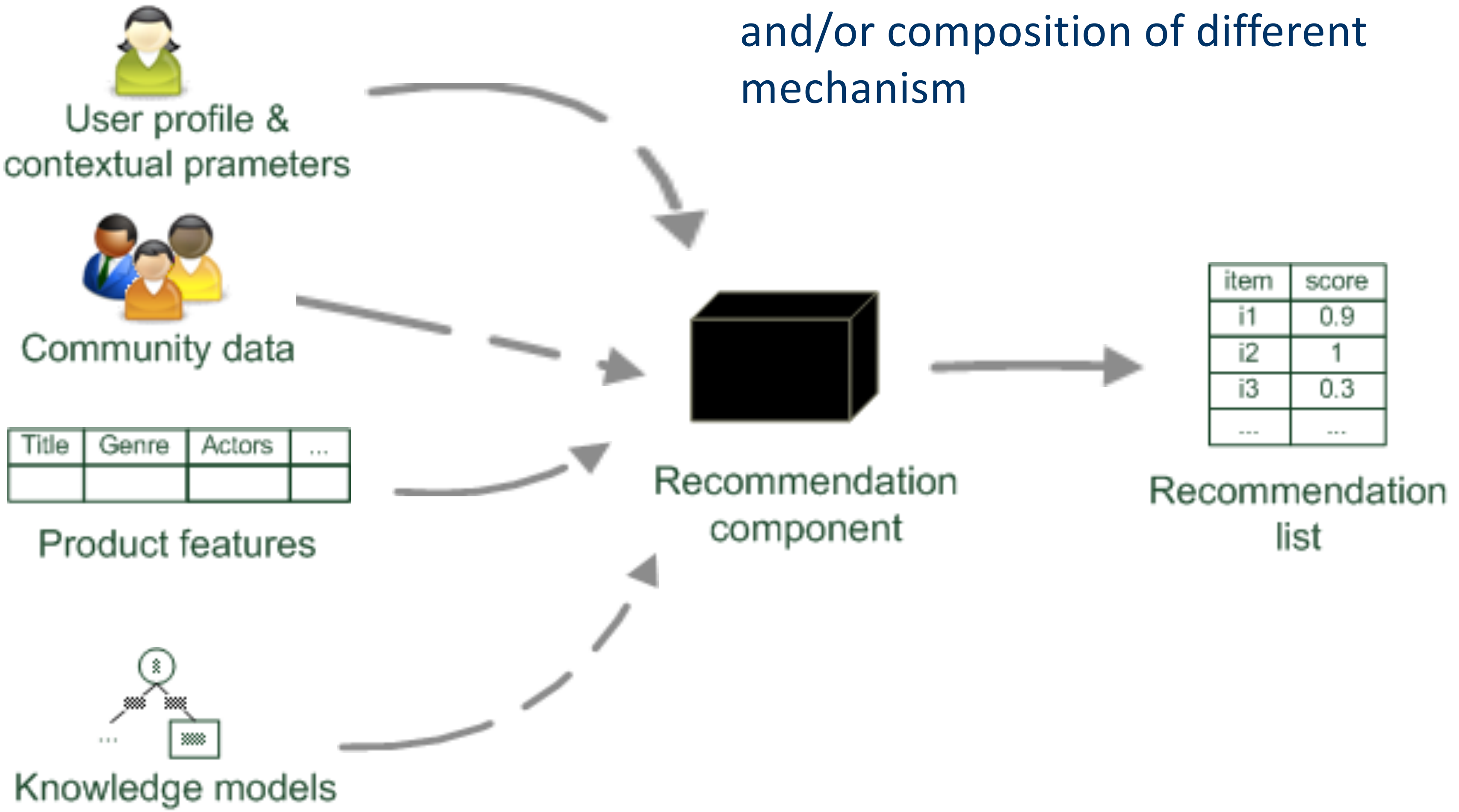
Paradigms of recommender systems

Knowledge-based: "Tell me what fits based on my needs"



Paradigms of recommender systems

Hybrid: combinations of various inputs and/or composition of different mechanism



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- introduction
- collaborative filtering
  - pure CF approaches
  - user-based nearest-neighbor
- evaluation
- data
- more algorithms
- challenges

pure CF approaches

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- Input
  - matrix of given user–item ratings
- Output types
  - degree to what the current user will like or dislike a certain item
  - a top-N list of recommended items

User\Item	Item 1	Item 2	Item 3	Item 4	...	....	Item N-2	Item N-1	Item N
User 1	1		1						
User 2				1				1	
User 3	1		1		1		1		
User 4									1
...									
...	1			1					
User M-2						1			
User M-1									1
User M		1				1			

User-based nearest-neighbor CF

- basic algorithm
  – given an "active user" u and an item i not yet seen by u
    - find a set of users (peers/nearest neighbors) who liked the same items as u in the past and who have rated item i
    - combine their ratings to predict, if u will like item i
      – e.g. average
  – … repeat do this for all items that u has not seen
  – recommend the best-rated items
- basic assumptions
  – if users had similar tastes in the past they will have similar tastes in the future
  – user preferences remain stable and consistent over time

User-based nearest-neighbor CF: example

	Item1	Item2	Item3	Item4	Item5
Alice	5	3	4	4	?
User1	3	1	2	3	3
User2	4	3	4	3	5
User3	3	3	1	5	4
User4	1	5	5	2	1

sim = 0,85

sim = 0,00

sim = 0,70

sim = -0,79

$$\boldsymbol{pred(u,p)} = \overline{\boldsymbol{r_a}} + \frac{\sum_{\boldsymbol{b} \in \boldsymbol{N}} \boldsymbol{sim(u,b)} * (\boldsymbol{r_{b,p}} - \overline{\boldsymbol{r_b}})}{\sum_{\boldsymbol{b} \in \boldsymbol{N}} \boldsymbol{sim}(u,\boldsymbol{b})}$$

- calculate whether the neighbors' ratings for the unseen item i are higher or lower than their average rating
- … weight, using the similarity with the active user, u, as a weight
- add/subtract the active user's average rating

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- introduction
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  - introduction
  - offline evaluation
  - metrics
  - online evaluation
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evaluate, we must…

- business questions
  - do customers like/buy recommended items?
  - do customers buy items they otherwise would have not?
  - are they satisfied with a recommendation after purchase?
- … lead to empirical evaluation
  - is the approach efficient with respect to a specific criteria like accuracy, user satisfaction, response time, serendipity, online conversion, ….
- ... during development and in deployment

… because the no-free-lunch theorem is out to get you!

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- many techniques available
  - [will be discussed in the next lesson]
- so…
  - which one is the best in a given application domain?
  - what are the success factors of different techniques?
  - comparative analysis based on an optimality criterion?

offline evaluation method

- data
  - collected in your problem
  - benchmark datasets

User\Item	Item 1	Item 2	Item 3	Item 4	…	….	Item N-2	Item N-1	Item N
User 1	1		1						
User 2				1				1	
User 3	1		1		1		1		
User 4									1
…									
…	1			1					
User M-2						1			
User M-1									1
User M		1				1			

train and test

- training set
  - randomly selected share of known **ratings**
  - build the model
- testing set
  - remaining share of withheld ratings
  - ground truth to evaluate the model's quality
  - … by comparing with its recommendations

- perhaps taking time into account rather than randomly

User\Item	Item 1	Item 2	Item 3	Item 4	...	....	Item N-2	Item N-1	Item N
User 1	1		1						
User 2				1				1	
User 3	1		1		1		1		
User 4									1
...									
...	1			1					
User M-2						1			
User M-1									1
User M		1				1			

… maybe with a twist

- training set
  - randomly selected share of known **users**
  - build the model
- testing set
  - remaining share of withheld users
  - recommendations based on observed items
  - … compared to hidden itens

- perhaps taking time into account rather than randomly
- … and removing useless data

User\Item	Item 1	Item 2	Item 3	Item 4	…	….	Item N-2	Item N-1	Item N
User 1	1		1						
User 2				1				1	
User 3	1		1		1		1		
User 4									1
…	1			1					
User M-2						1			
User M-1									1
User M		1				1			

Metrics

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- borrowing from information retrieval (IR)

		Reality	
		Actually Good	Actually Bad
Prediction	Rated Good	True Positive (tp)	False Positive (fp)
	Rated Bad	False Negative (fn)	True Negative (tn)

All recommended items

All good items

Precision and Recall

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- Recommendation is viewed as information retrieval task
  - i.e. retrieve (recommend) all items which are predicted to be "good"
- **Precision:** a measure of exactness, determines the fraction of relevant items retrieved out of all items retrieved
  - E.g. the proportion of recommended movies that are actually good

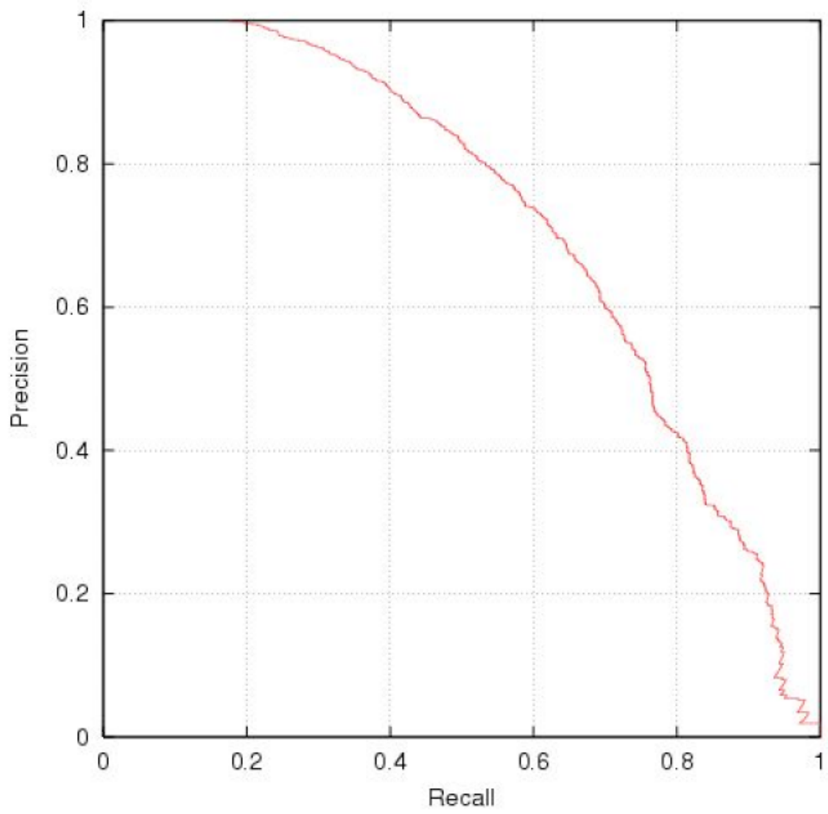
$$Precision = \frac{tp}{tp + fp} = \frac{|good\ movies\ recommended|}{|\text{all recommendations}|}$$

- **Recall:** a measure of completeness, determines the fraction of relevant items retrieved out of all relevant items
  - E.g. the proportion of all good movies recommended

$$Recall = \frac{tp}{tp + fn} = \frac{|good\ movies\ recommended|}{|all\ good\ movies|}$$

ROC, AUC and friends

- typically when a recommender system is tuned to increase precision, recall decreases as a result
  - or vice versa



F_1 Metric

- The **F_1 Metric** attempts to combine Precision and Recall into a single value for comparison purposes.
  – May be used to gain a more balanced view of performance

$$F_1 = 2 \cdot \frac{precision \cdot recall}{precision + recall}$$

- The F_1 Metric gives equal weight to precision and recall
  – Other F_β metrics weight recall with a factor of β.

ranks matter!

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For a user:

Actually good
Item 237
Item 899

hit

Recommended (predicted as good)
Item 345
Item 237
Item 187

- **Rank metrics** extend recall and precision to take the positions of correct items in a ranked list into account
  - Relevant items are more useful when they appear earlier in the recommendation list
  - Particularly important in recommender systems as lower ranked items may be overlooked by users

Rank Score

- extends the recall metric to take the positions of correct items in a ranked list into account
- the ratio of the Rank Score of the correct items to best theoretical Rank Score achievable for the user

$$rankscore = \frac{rankscore_p}{rankscore_{max}}$$

$$rankscore_p = \sum_{i \in h} 2^{-\frac{rank(i)-1}{\alpha}}$$

$$rankscore_{max} = \sum_{i=1}^{|T|} 2^{-\frac{i-1}{\alpha}}$$

Where:

- *h* is the set of correctly recommended items, i.e. hits
- *rank* returns the position (rank) of an item
- *T* is the set of all items of interest
- *α* is the *ranking half life*, i.e. an exponential reduction factor

Metrics: Normalized Discounted Cumulative Gain

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- Discounted cumulative gain (DCG)
  - Logarithmic reduction factor

$$DCG_{pos} = rel_1 + \sum_{i=2}^{pos} \frac{rel_i}{\log_2 i}$$

Where:

- *pos* denotes the position up to which relevance is accumulated
- rel_i returns the relevance of recommendation at position *i*

- Idealized discounted cumulative gain (IDCG)
  - Assumption that items are ordered by decreasing relevance

$$IDCG_{pos} = rel_1 + \sum_{i=2}^{|h|-1} \frac{rel_i}{\log_2 i}$$

- Normalized discounted cumulative gain (nDCG)
  - Normalized to the interval [0..1]

$$nDCG_{pos} \frac{DCG_{pos}}{IDCG_{pos}}$$

Example

- Assumptions:
  - |T| = 3
  - Ranking half life (alpha) = 2

Rank	Hit?
1	
2	X
3	X
4	X
5	

$$rankscore = \frac{rankscore_p}{rankscore_{\max}} \approx 0.71$$

$$rankscore_p = \frac{1}{2^{\frac{2-1}{2}}} + \frac{1}{2^{\frac{3-1}{2}}} + \frac{1}{2^{\frac{4-1}{2}}} = 1.56$$

$$rankscore_{\max} = \frac{1}{2^{\frac{1-1}{2}}} + \frac{1}{2^{\frac{2-1}{2}}} + \frac{1}{2^{\frac{3-1}{2}}} = 2.21$$

$$nDCG_5 \frac{DCG_5}{IDCG_5} \approx 0.81$$

$$DCG_5 = \frac{1}{\log_2 2} + \frac{1}{\log_2 3} + \frac{1}{\log_2 4} = 2.13$$

$$IDCG_5 = 1 + \frac{1}{\log_2 2} + \frac{1}{\log_2 3} = 2.63$$

Rankscore (exponential reduction) < NDCG (log. red.)

Average Precision

- ranked precision metric that places emphasis on highly ranked correct predictions (hits)
  - average of precision values determined after each successful prediction, i.e.

Rank	Hit?
1	
2	X
3	X
4	X
5	

$$AP = \frac{1}{3}\left(\frac{1}{2}+\frac{2}{3}+\frac{3}{4}\right) = \frac{23}{36} \approx 0.639$$

$$AP = \frac{1}{3}\left(\frac{1}{1}+\frac{2}{4}+\frac{3}{5}\right) = \frac{21}{30} = 0.7$$

Rank	Hit?
1	X
2	
3	
4	X
5	X

metrics for rating prediction

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- ground truth = ratings
  - i.e. regression problem
- Mean Absolute Error (MAE) computes the deviation between predicted ratings and actual ratings

$$MAE = \frac{1}{n}\sum_{i=1}^{n} | p_i - r_i |$$

- Root Mean Square Error (RMSE) is similar to MAE, but places more emphasis on larger deviation

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(p_i - r_i)^2}$$

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online evaluation: example

- Effectiveness of different algorithms for recommending cell phone games
  [Jannach, Hegelich 09]
- Involved 150,000 users on a commercial mobile internet portal
- Comparison of recommender methods
- Random assignment of users to a specific method

online evaluation: characteristics of methods

who is the **subject** that is in the focus of research?	online customers, students, historical online sessions, computers, …
what **research methods** are applied?	experiments, quasi-experiments, non-experimental research
in which **setting** does the research take place?	lab, real-world scenarios

Evaluation settings

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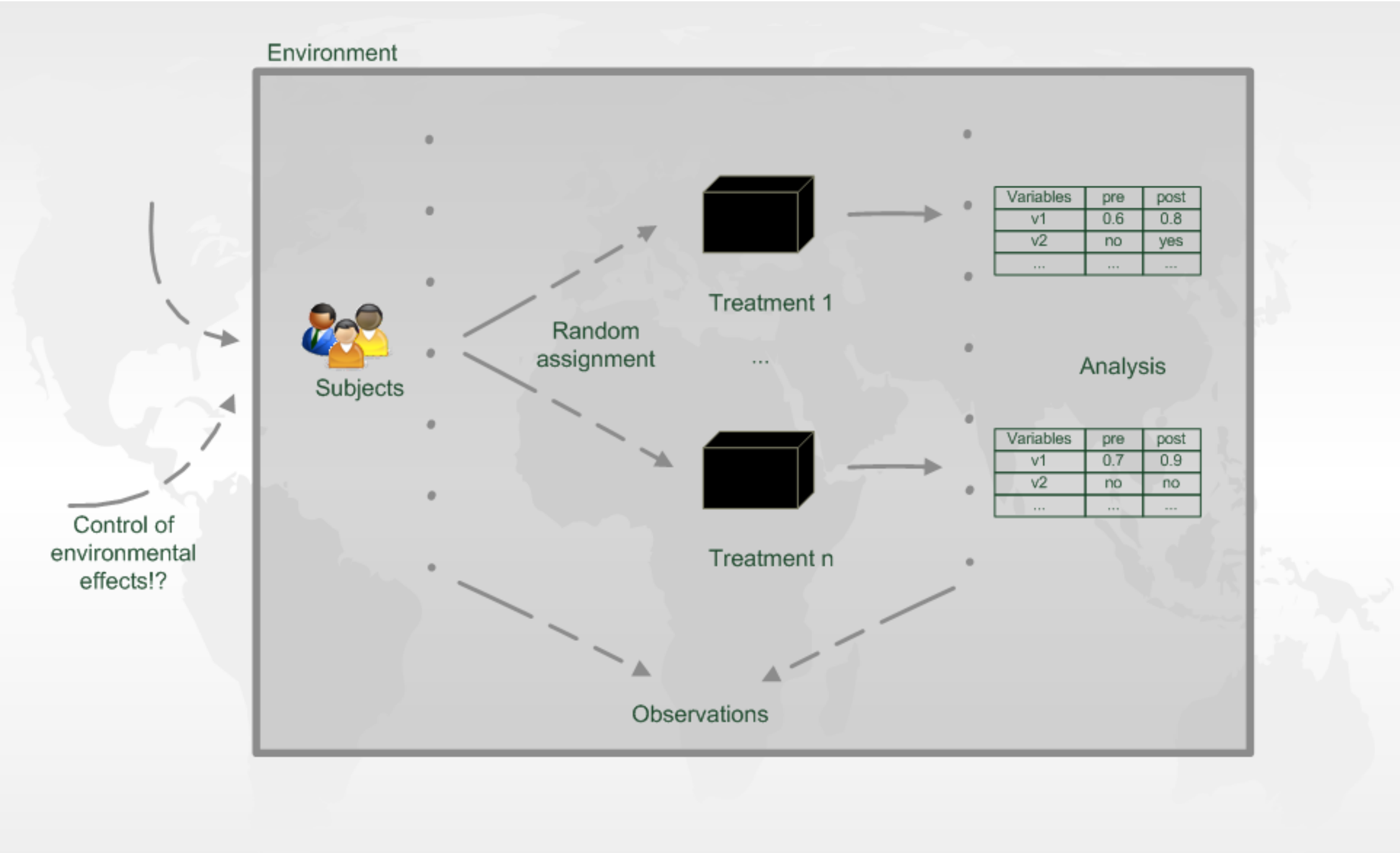
Lab studies	Field studies
• Expressly created for the purpose of the study • Extraneous variables can be controlled more easily by selecting study participants • ... who should behave as they would in a real-world environment • … but doubts may exist about participants motivated by money, prizes or social pressure	• Conducted in a preexisting real-world enviroment • Users are intrinsically motivated to use a system

experiment design: A/B testing



back to game recommendation: experimental design

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- Hypotheses on personalized vs. non-personalized recommendation techniques and their potential to
  - Increase conversion rate (i.e. the share of users who become buyers)
  - Stimulate additional purchases (i.e. increase the average shopping basket size)
- 155,000 visitors to site
  - split into 6 groups
  - ensure that customer profiles contained enough information (ratings) for all variants to make a recommendation
  - groups were chosen to represent similar customer segments
- catalog of 1,000 games
- five-point ratings scale ranging from -2 to +2 to rate items
  - due to the low number of explicit ratings, a click on the "details" link for a game was interpreted as an implicit "0" rating and a purchase as a "1" rating

Non-experimental research

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- Quasi-experiments
  - Lack random assignments of units to different treatments
- Non-experimental / observational research
  - Surveys / Questionnaires
  - Longitudinal research
    - Observations over long period of time
    - E.g. customer life-time value, returning customers
  - Case studies
    - Focus on answering research questions about how and why
    - E.g. answer questions like: *How recommendation technology contributed to Amazon.com‘s becomes the world‘s largest book retailer?*
  - Focus group
    - Interviews
    - Think aloud protocols

analysis of results in general

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- not different from other ML tasks

- are observed differences statistically meaningful or due to chance?
  - standard procedure for testing the statistical significance of two deviating metrics is the pairwise analysis of variance (ANOVA)

- … and are they of practical importance?
  - statistically significant doesn't mean important
  - what is the value to the organization?

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  - types of ratings
  - sparsity
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ratings: explicit vs implicit

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- explicit
  - typical choices:
    - 1 to 5, 1 to 7 Likert response scales
    - probably the most precise ratings
  - … possibly multidimensional
    - e.g. ratings for actors and sound as opposed to the movie
  - main challenge
    - users not always willing to rate many items
- implicit
  - user action interpreted as rating
    - e.g. access to content in social media
    - … access to product’s page and/or buying it
  - easy to collect transparently, without additional effort
  - main challenge
    - action doesn’t necessarily have the same meaning as a rating
      - e.g. user might not like all the books he or she has bought; the user also might have bought a book for someone else

User\Item	Item 1	Item 2	Item 3	Item 4	…	….	Item N-2	Item N-1	Item N
User 1	1		1						
User 2				1				1	
User 3	1		1		1		1		
User 4									1
…									
…	1			1					
User M-2						1			
User M-1									1
User M		1				1			

https://github.com/CSKrishna/Recommender-Systems-for-Implicit-Feedback-datasets

the truth about ground truth

[in RS, at least]

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- what is the meaning of an unknown?

Offline experimentation	Online experimentation
Ratings, transactions	Ratings, feedback
Historic session (not all recommended items are rated)	Live interaction (all recommended items are rated)
Ratings of unrated items unknown, but interpreted as “bad” (default assumption, user tend to rate only good items)	“Good/bad” ratings of not recommended items are unknown
If default assumption does not hold: True positives may be too small False negatives may be too small	False/true negatives cannot be determined
Precision may increase Recall may vary	Precision ok Recall questionable

data is sparse

[in RS, at least]

- natural datasets include historical interaction records of real users
  - what proportion of products from the Amazon catalog does a regular customer buy?
- sparsity can be measured
  - Sparsity = $1 - |R|/|I| \cdot |U|$
  - R = ratings
  - I = items
  - U = users

User\Item	Item 1	Item 2	Item 3	Item 4	...	....	Item N-2	Item N-1	Item N
User 1	1		1						
User 2				1				1	
User 3	1		1		1		1		
User 4									1
...									
...	1			1					
User M-2						1			
User M-1									1
User M		1				1			

https://github.com/CSKrishna/Recommender-Systems-for-Implicit-Feedback-datasets

the problems with sparsity

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- how many items in common are two users expected to have?
  - so, how likely are patterns with large statistical support?

- additional (very interesting!) problem
  - cold start problem
    - how to recommend new items?
    - what to recommend to new users?
  - some (simple) approaches
    - ask/force users to rate a set of items
    - in the beginning, use method not based on ratings
      - … then CF method
    - default voting
      - assign default values to items that only one of the two users to be compared has rated
  - more complex algorithms exist

User\Item	Item 1	Item 2	Item 3	Item 4	...	....	Item N-2	Item N-1	Item N
User 1	1		1						
User 2				1				1	
User 3	1		1		1		1		
User 4									1
...									
...	1			1					
User M-2						1			
User M-1									1
User M		1				1			

https://github.com/CSKrishna/Recommender-Systems-for-Implicit-Feedback-datasets

… also for evaluation

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Nr.	UserID	MovieID	Rating (r_i)	Prediction (p_i)	$\|p_i-r_i\|$	$(p_i-r_i)^2$
1	1	134	5	4.5	0.5	0.25
2	1	238	4	5	1	1
3	1	312	5	5	0	0
4	2	134	3	5	2	4
5	2	767	5	4.5	0.5	0.25
6	3	68	4	4.1	0.1	0.01
7	3	212	4	3.9	0.1	0.01
8	3	238	3	3	0	0
9	4	68	4	4.2	0.2	0.04
10	4	112	5	4.8	0.2	0.04
					4.6	5.6

MAE = 0.29
RMSE = 0.42

MAE = 0.46
RMSE = 0.75

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- more algorithms
  - more about CF approaches
  - content-based
  - knowledge-based
  - hybrid approaches
- challenges

Memory-based and model-based approaches

- User-based CF is a memory-based approach
  - the rating matrix is directly used to find neighbors / make predictions
  - does not scale for most real-world scenarios
- Model-based approaches
  - based on an offline pre-processing or "model-learning" phase
  - at run-time, only the learned model is used to make predictions
  - models are updated / re-trained periodically

More model-based approaches

- Matrix factorization techniques, statistics
  - singular value decomposition, principal component analysis
- Association rule mining
  - compare: shopping basket analysis
- Probabilistic models
  - clustering models, Bayesian networks, probabilistic Latent Semantic Analysis
- Various other machine learning approaches

Matrix factorization

- (Golub and Kahan 1965) a given matrix M can be decomposed into a product of three matrices as follows

$$M = U \times \Sigma \times V^T$$

  – where U and V are called *left* and *right singular vectors* and the values of the diagonal of Σ are called the *singular values*

- full matrix can be approximated by observing only the most important features
  – those with the largest singular values

Example for SVD-based recommendation

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- SVD: $M_k = U_k \times \Sigma_k \times V_k^T$

U_k	Dim1	Dim2
Alice	0.47	-0.30
Bob	-0.44	0.23
Mary	0.70	-0.06
Sue	0.31	0.93

V_k^T	Terminator	Die Hard	Twins	Eat Pray Love	Pretty Woman
Dim1	-0.44	-0.57	0.06	0.38	0.57
Dim2	0.58	-0.66	0.26	0.18	-0.36

Σ_k	Dim1	Dim2
Dim1	5.63	0
Dim2	0	3.23

- Prediction: $\hat{r}_{ui} = \bar{r}_u + U_k(Alice) \times \Sigma_k \times V_k^T(EPL)$

= 3 + 0.84 = 3.84

projection of U and V^T in the 2 dimensional space (U_2, V_2^T)

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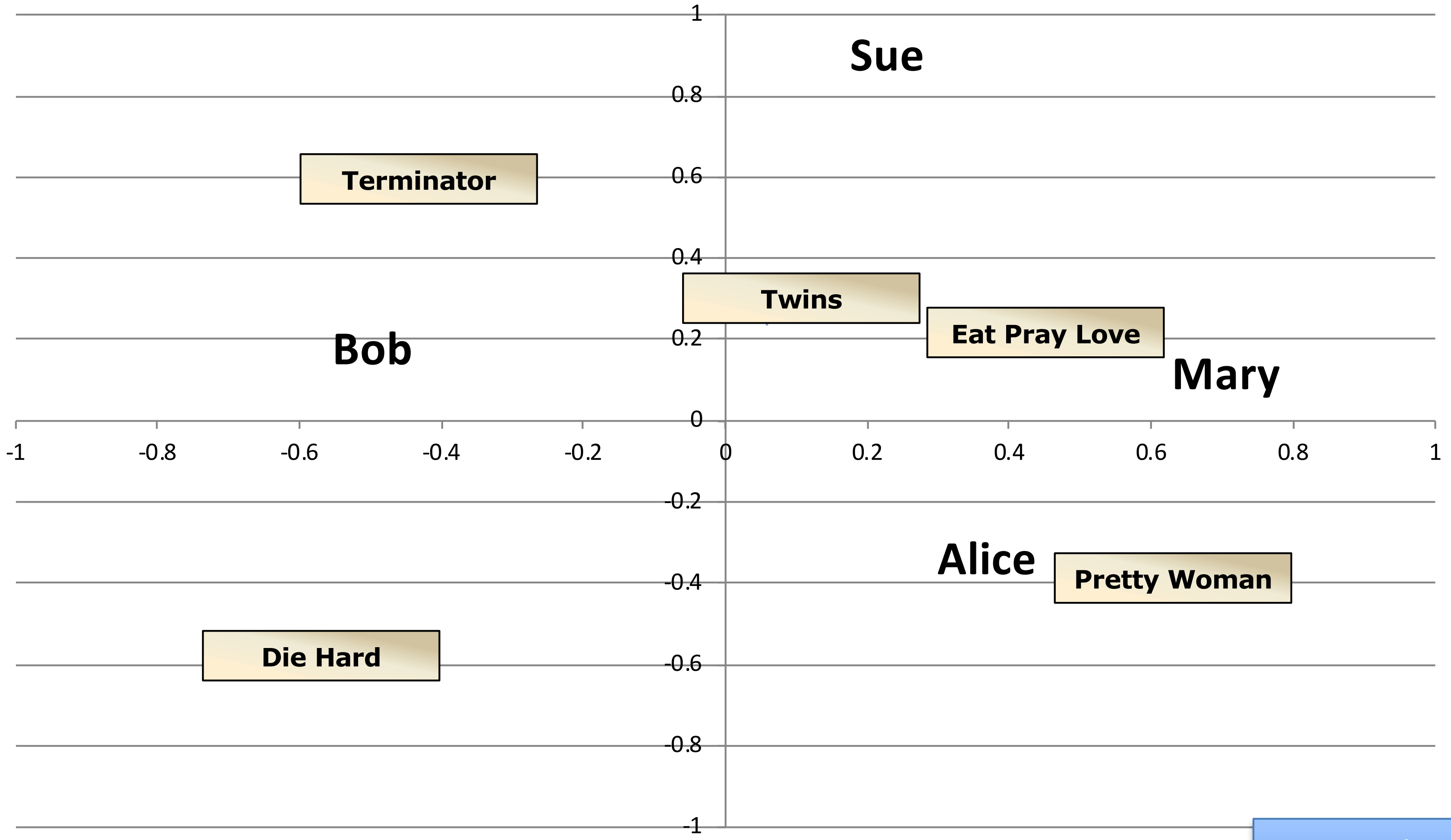

remember PCA?

Content-based recommendation

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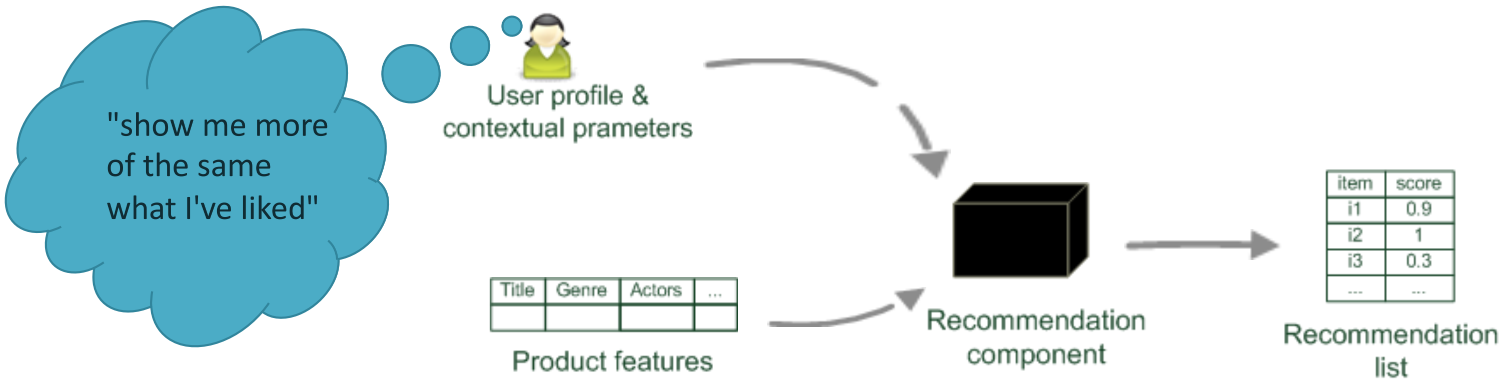
- **While CF – methods do not require any information about the items,**
  - it might be reasonable to exploit such information; and
  - recommend fantasy novels to people who liked fantasy novels in the past
- **What do we need:**
  - some information about the available items such as the genre ("content")
  - some sort of *user profile* describing what the user likes (the preferences)
- **The task:**
  - learn user preferences
  - locate/recommend items that are "similar" to the user preferences



what is the "content"?

- often, a combination of attributes and (semi-)free text
  - e.g. book recommendation

Title	Genre	Author	Type	Price	Keywords
The Night of the Gun	Memoir	David Carr	Paperback	29.90	Press and journalism, drug addiction, personal memoirs, New York
The Lace Reader	Fiction, Mystery	Brunonia Barry	Hardcover	49.90	American contemporary fiction, detective, historical
Into the Fire	Romance, Suspense	Suzanne Brockmann	Hardcover	45.90	American fiction, murder, neo-Nazism

- recommendation approach
  - related to NLP and document classification
  - … out of the scope of this course

knowledge-based recommendations

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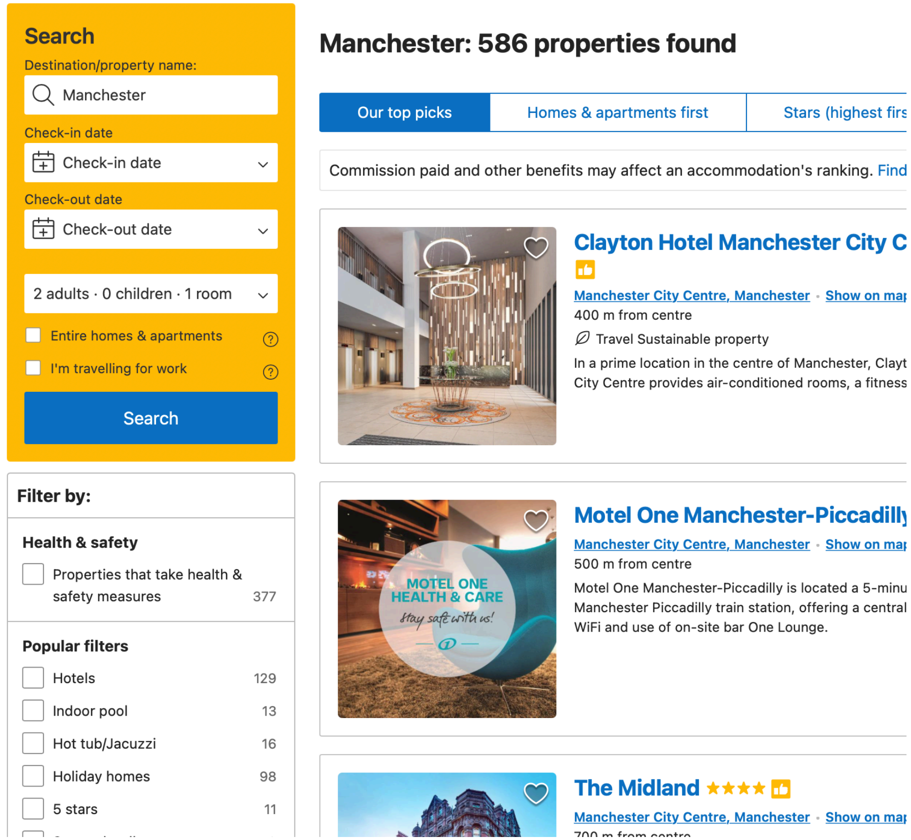
- users want to define their requirements explicitly
  - ”the accomodations should be pet-friendly"
- time span plays an important role
  - e.g. five-year-old ratings for computers are hardly useful
  - … or user lifestyle or family situation changes
- items with low number of available ratings
  - typically



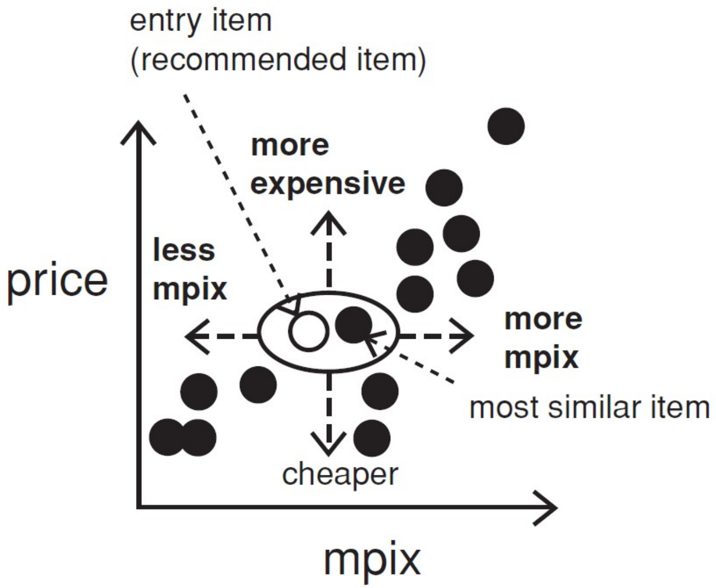
knowledge-based RS

- Constraint-based
  - based on explicitly defined set of recommendation rules
  - fulfill recommendation rules
- Case-based
  - based on different types of similarity measures
  - retrieve items that are similar to specified requirements

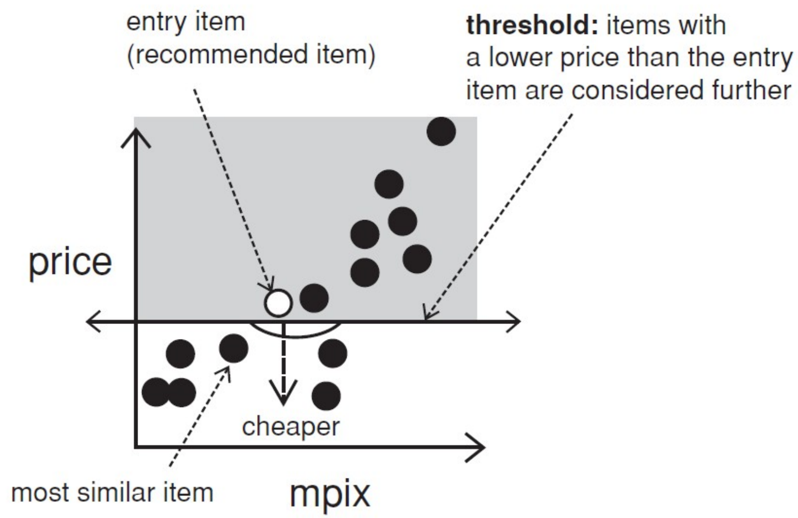
- Both approaches are similar in their conversational recommendation process
  - users specify the requirements
  - systems try to identify solutions
  - if no solution can be found, users change requirements

interaction with knowledge-based RS: critiquing

- user may not know exactly what they are seeking
- … can specify their why current item is not satisfactory
  – e.g. price must be lower

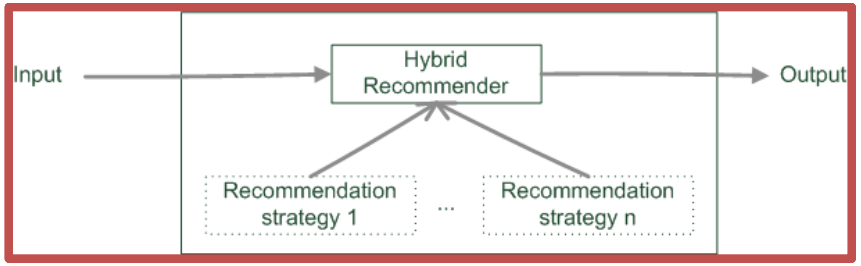


Critique on price

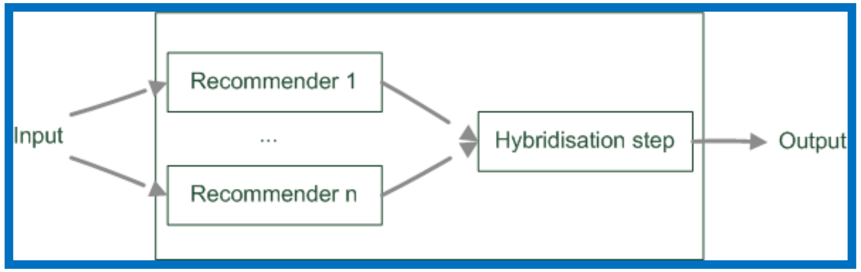


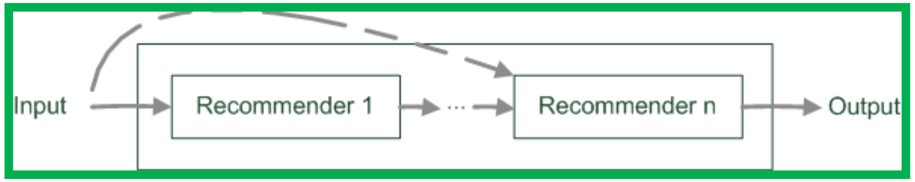
hybrid recommender systems

- think of the best salesperson you have met
  - probably combines ideas from the three approaches discussed



- hybridization
  - monolithic exploitation of different features
  - parallel
  - pipeline



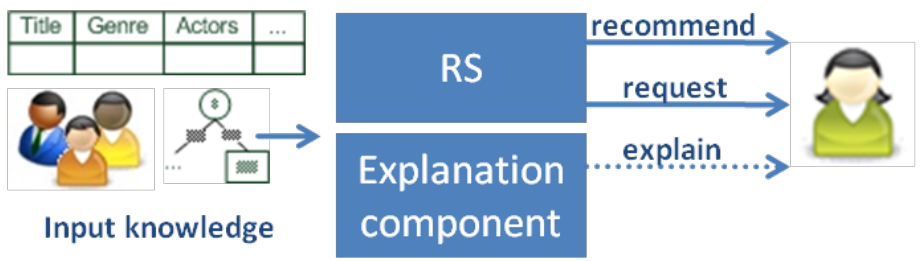


gps

- introduction
- collaborative filtering
- evaluation
- data
- more algorithms
- challenges
  - explaining recommendations
  - attacks
  - ubiquitous recommendations

explanation in recommender systems

- "The digital camera *Profishot* is a must-buy for you because . . . ."
- two parties involved
  - organization interested in convincing user
  - user concerned about making the right choice(s)



attacks

- (monetary) value of being in recommendation lists
- attacks aim to
  - push some items
  - sabotage other items
  - simply sabotage the system
  - manipulation the ”internet opinion"

example: profile injection

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- e.g. memory-based CF with 1 neighboor
  - i.e. only opinion of most similar user will be used to make prediction

	Item1	Item2	Item3	Item4	…	Target	Similarity
Alice	5	3	4	1	…	**?**	
User1	3	1	2	5	…	5	-0.54
User2	4	3	3	3	…	2	0.68
User3	3	3	1	5	…	4	-0.72
User4	1	5	5	2	…	1	-0.02
Attack	**5**	**3**	**4**	**3**	**…**	**5**	**0.87**

← User2 most similar to Alice

← Attack most similar to Alice

Attack

ubiquitous RS: there's an app for it

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- mobile applications have been a domain for recommendation
  - small display sizes and space limitations
  - naturally require personalized information
  - used "on the go"

context-aware recommendation

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- (Ranganathan and Campbell, 2003) context
  - "any information about the circumstances, objects or conditions surrounding a user that is considered relevant to the interaction between the user and the ubiquitous computing environment"
- (Shilit et al., 1994) most important aspects of context as
  - where you are
  - who you are with
  - what resources are nearby

research questions in ubiquitous domains

- goals
  - serendipitous recommendations vs proximity?
- role of contextual parameters, such as location
  - another preference
  - a requirement that is always strictly enforced, or
  - something in between?
- modality of interaction, for users "on the go"
  - pushing information is useful to draw recipients' attention
  - … but may be invasive

application domains

- M-Commerce
  - m-commerce refers to monetary transactions that are conducted via wireless networks.
- Tourism and visitor guides
  - travelers have specific information needs, makes this domain a natural choice for mobile information systems.
- Cultural heritage and museum guides
  - mobile guides for archeological sites or museums providing multimedia services.
- Home computing and entertainment
  - users are able to personally configure and adapt smart devices in their environment based on their preferences and on specific situations.

discussion & summary

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- problem of recommendation
- collaborative filtering approaches
- … and other algorithms
- evaluation is key! (once more…)
  - metrics
  - ... use of data for estimating their value
- issues of the data used in RS
- … other challenges